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Quantifying spatial disparities and influencing factors of home, work, and activity space separation in Beijing

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ABSTRACT

Due to rapid informatization and increasing urban sprawl, currently, metropolitan residents are facing challenges regarding spatial imbalance between their home, workplace, and activity locations, which seriously affects the quality of life and subjective well-being of urban residents. However, only a few existing studies have analyzed the relationship between home, workplace, and other activity spaces of urban residents and the influence mechanism of spatial separation of the three locations. In this study, we used the mobile phone signaling data of the residents of Beijing for May 2019 to explore the degree of mutual separation of the three locations, based on the identification of the homes, workplaces, and main activity spaces of over 2.3 million residents in Beijing. Leveraging these data, we discussed the influence mechanism of activity separation, in terms of the built environment and socioeconomic factors. The results indicated that the degree of the home-workplace separation was the highest, followed by the home-workplace-activity space separation, and the home-activity space separation was the lowest. Notably, the three types of spatial separations had significant spatial disparities. Attribution analysis indicated housing price as the dominant factor affecting the spatial separation of the residents, while the accessibility and location also having important effects. Moreover, the interaction of these factors had a stronger explanatory power for the spatial separation of the daily activity spaces of the urban residents. This study is the first to estimate the degree of spatial separation among the homes, workplaces, and other activity spaces of urban residents and analyzed their correlation using geographic context factors. Our results can provide useful scientific insights to explore the spatial characteristics of the home-work-activity relationship with respect to metropolitan residents and optimize the spatial distribution of urban functions.

1. Introduction

"Activity space" refers to a set of places that individuals encounter during their routine activities, where regular events occur with distinctive rhythms and timings (Golledge & Stimson, 1997). This space can truly reflect the use of urban space, time, and quality of life of an individual, which is a fundamental concern and important perspective in urban studies, and is widely used in urban socio-spatial segregation, social equity, life quality, accessibility, and other research fields (Schönfelder & Axhausen, 2003; Järv, Müürisepp, Ahas, Derudder, & Witlox, 2015). In recent years, due to rapid globalization and informatization, as well as the development in mobile technology, the routine activities of most individuals have been greatly affected, and the activity spaces and patterns have changed dramatically as well (Schwanen & Kwan, 2008). Consequently, the complexity of daily activities of residents and the underlying rules of spatial organization have attracted a wide range of attention in many interdisciplinary fields, including geography, urban planning, transportation, and society (Cagney, York Cornwell, Goldman, & Cai, 2020; Hu, Li, & Ye, 2020; Pollard, Engelen, Held, & de Dear, 2022). The relevant research results can not only provide important scientific guidance and decision-making support for daily travel, public health management, and living space

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optimization of residents, but also improve the scientific understanding of urban spatial structure performance and its impact mechanism (Brockmann, Hufnagel, & Geisel, 2006; Zenk et al., 2011).

Existing studies have revealed that people always carry out their daily lives around their residences, among which everyday living and work are the most important daily activities having strong spatiotemporal patterns (Isaacman et al., 2011; Sevtsuk & Ratti, 2010). Therefore, existing studies focused on the residential and employment spaces from the perspective of job-housing relationships (Zheng, Zhou, & Deng, 2021). However, existing reports indicated that commuting trips accounted for only 42.3% of the daily trips of resident, while the proportion of non-commuting trips exceeded 50%, while portraying a tendency to increase year after year (Beijing Transport Institute, 2020). Meanwhile, due to the growth in globalization and informatization, daily lives and activity patterns of the residents are facing great changes. In particular, residents' living needs and travel ability have been greatly improved with the increasing development of information and communications technology (ICT) and economic level (Schwanen & Kwan, 2008). Notably, their daily activities are no longer constrained by the traditional geographical distance, and the activity types and spaces have evolved to become increasingly rich and free, compared to the previous simple linear relationship between specific locations. Therefore, residents' daily activity and activity spaces are increasingly complex, diversified, and personalized (Shen & Chai, 2018). However, due to rapid informatization and increasing urban sprawl, currently, metropolitan residents are facing challenges regarding spatial imbalance between their home, workplace, and activity locations, which seriously affects the quality of life and subjective well-being of urban residents. In this context, as an important part of urban residents' daily life, the non-home-working spaces (NHWS) and their interrelationships with homes and workplaces deserve more attention, and the influencing mechanism of the spatial relationship of these three types of live spaces also needs to be further explored.

The remainder of this paper is organized as follows. Section 2 reviews the literature on the resident activity space and spatial separation and its influencing factors, puts forward the theoretical framework of this study. Section 3 introduces the study area and data collection methods, and the analytical framework of this study are presented in Section 4. Section 5 provides three main empirical results: travel characteristics and home-workplace-activity space separations at the subdistrict scale and different groups, and the influencing factors of home-workplace-activity space separation. Finally, the conclusions of this paper are drawn and future research directions are proposed in Section 6.

2. Literature review

2.1. Resident activity space studies

Resident activity space studies can be traced back to the field of temporal and behavioral geography (Hägerstrand, 1970), which was formed in the 1960s and 1970s, and involve many aspects of the daily life of an individual, e.g., their residential, commuting, and shopping areas. In the traditional activity space studies, the research data were mainly collected by means of census, travel surveys, questionnaires, and interviews. On this basis, scholars have conducted extensive research explorations on individual spatiotemporal paths and potential activity spaces (Miller, 1991; Newsome, Walcott, & Smith, 1998), routine activity areas, and accessibility (Casas, 2007; Sherman, Spencer, Preisser, Gesler, & Arcury, 2005), as well as the activity patterns of specific groups and spatial segregation (Schönfelder & Axhausen, 2003; Wong & Shaw, 2011). Most previous studies demonstrated that residents' daily activity spaces and activity patterns have great habituality and regularity (Ewing & Cervero, 2001; Maat, van Wee, & Stead, 2005). However, the quality of data from activity-diary surveys is largely limited by the rationality and validity of the questionnaire design and the way it is distributed, and the spatiotemporal scale of the sample distribution are often small (Hasan, Zhan, & Ukkusuri, 2013, August; Ríos & Muñoz, 2017). Therefore, in the context of rapid urbanization and informatization, the traditional activity space research paradigm cannot effectively capture new developmental trends and dynamics, which cannot support the in-depth exploration of activity spaces of the residents and their spatial organization relationships in the new era.

In contrast, recent progress in the development of mobile internet and various sensing technologies has led to the emergence of spatiotemporal big data. It has become possible to obtain massive, dynamic, and fine-grained individual/group mobility information (Barabasi, 2005; Liu et al., 2015), thus, providing good opportunities for activity space analyses. The emergence of various big data provides a wide range of data sources, such as mobile phone data (Silm & Ahas, 2014), smart card data (Zhang, Yang, Zhen, Lobsang, & Li, 2021), floating vehicle data (Erdelić et al., 2021), and social media data (Hu, Li, & Ye, 2020), for activity space studies. It provides a new route toward facilitating fine-grained and multi-scale spatial studies of the activities of the residents. Notably, the multidisciplinary intersection of geographic information science, behavioral geography, statistical physics, complex network science, and computer science in the big data era supports the quantification of activity space studies (Liu, Huang, Gao, & Xia, 2021; 2021b). In this context, researchers have carried out extensive practical explorations in the field of activity space research, based on various emerging spatiotemporal big data, including activity space identification, activity pattern discovery, activity space structure, and dynamics (Järv, Ahas, & Witlox, 2014; Chen, Hui, Wu, Lang, & Li, 2019; Comber, Park, & Arribas-Bel, 2022).

However, in terms of research content, previous studies paid relatively little attention to the activities of residents that are not related to their home or work, and most of them only focused on single types of activities (e.g., recreation, shopping, and eating) and its spatial distribution (Liu, Long, Zhang, & Liu, 2021; Scott & He, 2012). In addition, most previous studies focused on the spatial distribution and patterns of resident activity from the perspective of scale and density, whereas little attention has been paid to the interrelationship between different types of activity spaces from the perspective of spatial interaction. At the same time, existing studies do not have a clear and uniform definition of NHWS, and lacking theoretical and empirical cases of this type of space. Therefore, the NHWS of urban residents and their interrelationships with home and workplaces deserve more attention and in-depth exploration.

2.2. Spatial separation and its influencing factors: from jobs-housing mismatch to home-working-activity spatial separation

The concept of *Spatial Separation* or *Spatial Mismatch* can be traced back to the Spatial Mismatch Hypothesis (SMH) proposed by Kain in 1968, which initially mainly referred to the spatial mismatch of urban residents' residence and employment in the context of rapid urbanization and suburbanization (Kain, 1968). Then, SMH has triggered extensive thinking in the academia, and different scholars have successively verified it from different perspectives, and have achieved rich research results in theoretical and empirical studies on the SMH, job-housing balance, and excess commuting (Hu & Wang, 2015; Hui, Zhong, & Yu, 2015; Liu, Zhang, & Feng, 2021). Moreover, with the continuous development of suburbanization and the expansion of research perspectives, researchers have gradually recognized that spatial separation is essentially a general phenomenon of unequal spatial opportunities due to the reorganization of urban functions and spatial reconfiguration (Houston, 2005; Hu, 2015).

In terms of research content, the existing spatial separation studies have mainly verified or measured the separation degree between homes and workplaces of urban residents, and the formation mechanism and influencing factors of home-working spatial separation from the perspectives of time, distance, and accessibility (Hu, Li, & Ye, 2020; Long &

Thill, 2015; Yao & Wang, 2018). However, NHWS is often neglected in spatial separation studies. Additionally, separation between the homes and workplaces is only part of urban residents' daily life (Zhang, Wang, & Kan, 2022), therefore, the spatial separation research should not only focus on the homes and workplaces of urban residents but also pay more attention to the interrelationship and separation degree between NHWS and homes and workplaces.

In addition, regarding the formation mechanism and influencing factors of spatial separation, scholars have mostly used traditional data (questionnaire surveys, census data, etc.) or emerging big data to reveal the important influence of basic resident attributes and some built environment factors on the home-working spatial separation (Ewing & Cervero, 2001; Shen, Ta, & Liu, 2021). For example, existing studies have demonstrated that transportation, ethnicity, neighborhood-built environment, and other socioeconomic attributes are closely related to residents' life patterns and spatial organization (Ewing & Cervero, 2010; Lyons & Ewing, 2021; Tan, Kwan, & Chai, 2017; Xu et al., 2016). In particular, the neighborhood land-use patterns of high-density, dense road networks, and high accessibility of facilities compress the spatio-temporal distance between different destinations and profoundly affect the daily activities and spatial patterns of urban residents (Cao & Fan., 2012; Fan & Khattak, 2008). However, most of the existing studies have focused only on the independent effects of various factors on spatial separation. Nonetheless, as a complex urban problem, the generation and development of spatial separation is the result of the joint influence of various factors. Considering only the independent effects of various influencing factors on spatial separation may have certain limitations in spatial separation research. Therefore, based on revealing the independent effects of various influencing factors on the spatial separation of residents' daily lives, this study will further explore the comprehensive effects of various factors' interaction on spatial separation, to provide a more comprehensive explanation for the influence mechanism of spatial separation.

Accordingly, based on the above literature review and research summary, we found two main gaps in the activity space research. First, NHWS and their interrelationships with home and workplaces are often neglected in the activity space research. Second, most of the existing studies of the influencing factors of spatial separation have focused only on the independent effects of various factors, and the exploration of multi-factor interactions is lacking. To fill the above research gap, the research objectives of this study included two main aspects. On the one hand, the three major components of residential living space (i.e., home, workplace, and other activity spaces not related to home or work) were analyzed, along with their interrelationships. For the convenience of expression, other activity spaces of the resident not related to home or work are referred to as "activity space" in this manuscript. Thus, we defined and identified the home, workplace, and activity spaces, based on the mobile phone signaling data of the city. On this basis, we explored the interrelationship between the three most important spaces in the daily lives of residents (i.e., home, workplace, and activity space) and the urban spatial structure patterns they reflect. On the other hand, the Geodetector model was used to conduct attribution analysis and explore the influence mechanism of the separation of the home, work, and activity spaces from the perspectives of built environment and socioeconomic attributes. Ultimately, the aim of our study is to improve the scientific understanding of the interrelationship of the three major living spaces (Fig. 1).

3. Study area and data

3.1. Study area

As a world-class metropolis and the capital city of China, Beijing is not only a political but also a cultural center. Our study area consisted of the urban area within the 6th ring road of Beijing, which is a relatively homogeneous and highly urbanized area. It includes 12 districts and 188 subdistrict units (Fig. 2). According to the Beijing Transport Development Annual Report 2020 (Beijing Transport Institute, 2020), the study area accounts for 79% and 78% of the residential population and jobs in Beijing in 2019, respectively, indicating that the study area is a major host area for population distribution and socioeconomic activities. Currently, as an international metropolis, Beijing is facing a developmental dilemma due to high population density and shortage of space resources in the central city. Therefore, the Beijing Municipal Government is actively promoting the decentralization of population and non-capital functions in the central urban district to optimize the urban spatial structure and construct a livable city. Consequently, it is of great theoretical and practical significance to strengthen the study of daily activity spaces of residents in the core urbanized areas of Beijing, to interpret the spatial organization of urban daily life in Beijing, optimize and enhance urban functions, and promote the construction of a world-class harmonious and livable city.

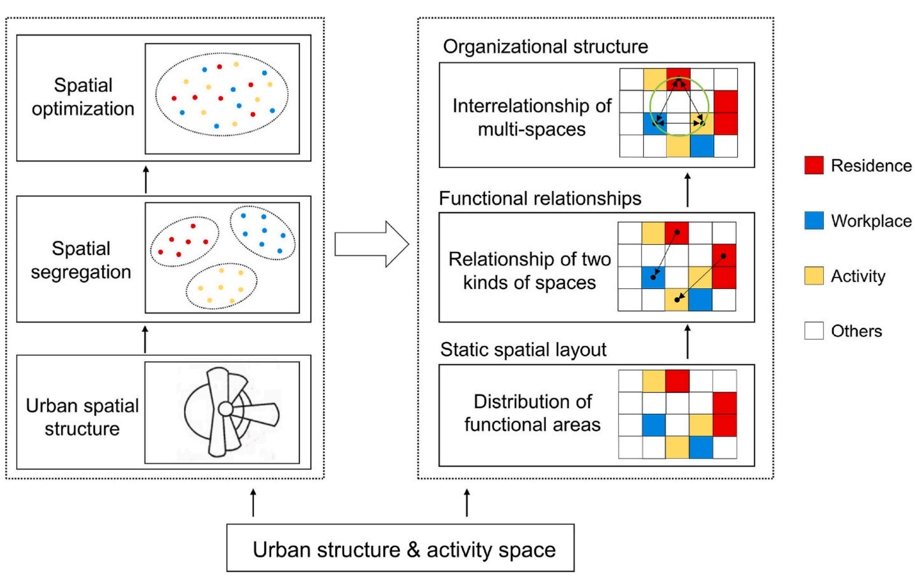

Fig. 1. Conceptual framework of this study.

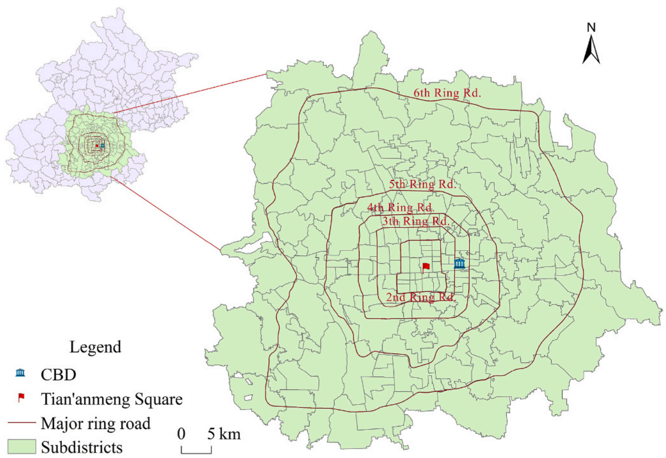

Fig. 2. Map of study area, with subdistricts and ring roads.
*Note: central business district (CBD); Road (Rd.).

3.2. Data

The data used in our study included the mobile phone, point of interest (POI), road network, and other socioeconomic data. Among them, the mobile phone data were the aggregated data of Beijing for May 2019 that was provided by the Smartsteps (www.smartsteps.com), which is a big data technology provider. The data included user personal attributes (gender and age), movement and stay information, stay type (0: visit, 1: residence, 2: employment), and stay frequency, along with other related information. The stay data included the location data of the first location in the morning, the last location in the evening, and the location data for the rest of the time when multiple signaling was triggered at the same location and the starting and ending intervals were more than 30 min. Each location corresponded to a 100 × 100 m grid, and the location point to location point was regarded as movement.

The POI data were collected from an Internet digital map (https://lbs.amap.com/), it contained 897,404 POIs, including the POI ID, name, longitude, latitude, and category. The road network data were obtained from OpenStreetMap (https://www.openstreetmap.org/), with corresponding data cleaning and deduplication. In addition, several socioeconomic data, including population density and structure, employment density, and income, were used in our study, these were obtained from the Beijing Public Data Open Platform (data.beijing.gov.cn), Fourth Economic Census Bulletin, and the Gazette of the Seventh National Population Census for Beijing Municipality published on the official website of the Beijing Municipality (http://www.beijing. gov.cn).

4. Methodology

This section describes the analytical framework used in our study. It included four steps (Fig. 3): (1) mobile phone data was collected from Smartsteps, and the data was then cleaned and pre-processed; (2) we identified the home (H), workplace (W), and major activity places (A) of every mobile phone user, based on their monthly stay time and stay frequency; (3) the movement distance and radius of gyration of the daily activities of residents were measured, while quantifying three separation indicators, that is, home-workplace separation (HWS), home-activity space separation (HAS), and home-workplace-activity space separation (HWAS), and exploring the spatial distribution characteristics of these three separations; and (4) the geodetector model was used to analyze the influence mechanism of H–W-A spatial separation from the perspectives of built environment and socioeconomic attributes.

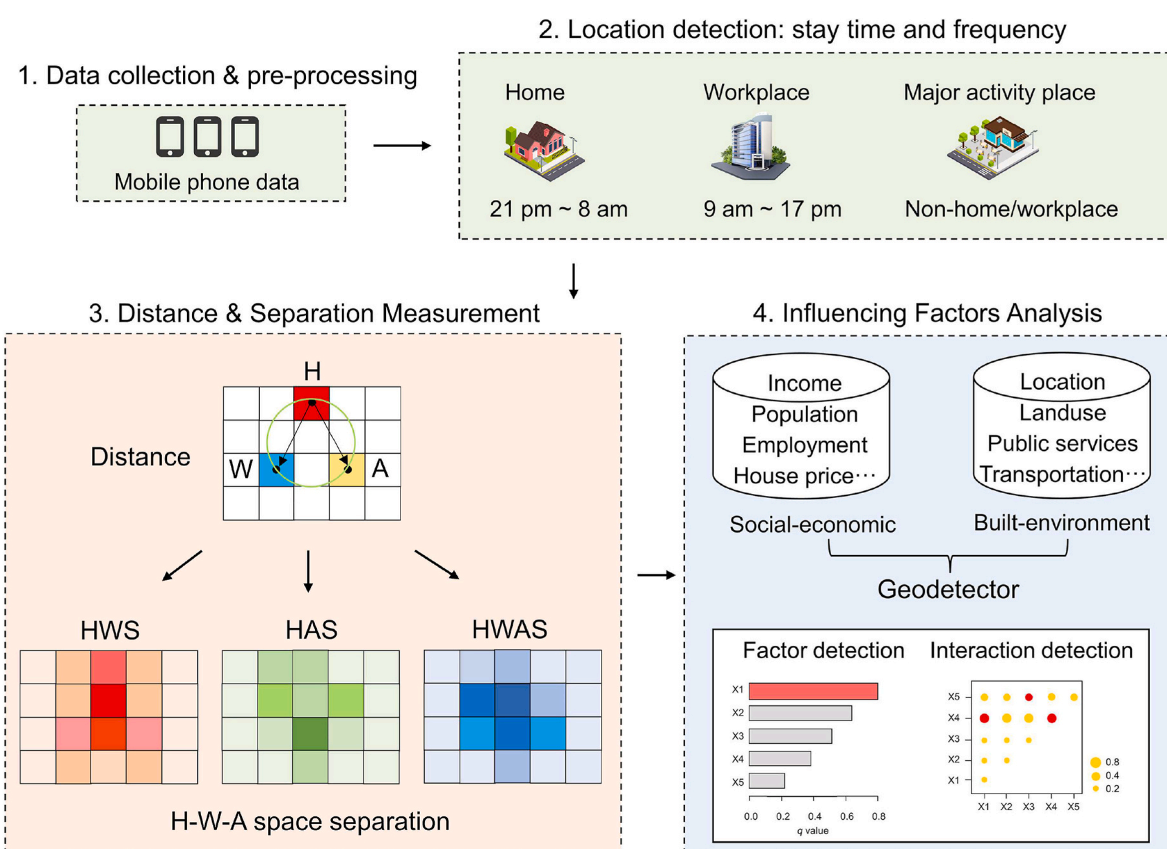

Fig. 3. Analytical framework of this study.

4.1. Location detection: home, workplace, and major activity space

In daily life, an individual always start from home to reach an activity location as their destination. Generally, home and work are the most dominant daily activities, and their spatiotemporal regularity is extremely strong. Thus, they can be identified by mobile phone data. In this study, we referred to existing methods to identify the users' homes and workplaces based on their stay time and frequency (Xu et al., 2015; Zou, Zhang, & Zhen, 2021). Specifically, "home" was identified as the place where the user stayed for the longest period of time from 21:00 h to 08:00 h in a month. The workplace was identified as the place where the user had the longest stay time between 09:00 h and 17:00 h in a month. Notably, we were able to identify the homes and workplaces of 2,343,405 users in the study area.

To verify the representativeness of the mobile phone users, the identified users' homes were counted in each subdistrict and compared with the populations of each subdistrict in the Gazette of the Seventh National Population Census for Beijing Municipality. The correlation coefficient between the mobile phone data and the statistics was 0.776 (0.01), indicating that the identified user information was highly representative. Furthermore, to extract the stable activity space of the user, based on the identification of their home and workplace, the other location where the user stayed most frequently (at least five times in a month and the stay time exceeds 0.5 h each time) in a month was regarded as the major activity space. Based on this, a user dataset was constructed, based on individual user attributes, H, W, and A (Table 1).

4.2. Calculation of movement range: distance and radius of gyration

Home is a key anchor point of daily activities of people and has been used as an important reference point when analyzing human activity patterns (Xu et al., 2015). In this study, we calculated the movement distance and radius of gyration of the user with reference to their home as the anchor point to analyze the population travel characteristics. The results were aggregated to the subdistricts. Among them, movement distance was the basic index to describe the population travel characteristics, using which, we measured the home-working distance (HWD) and home-activity distance (HAD). The radius of gyration (R_g) has been widely applied in activity-based research to describe the individual activity spaces and living ranges (Gonzalez, Hidalgo, & Barabasi, 2008; Xu, Belyi, Bojic, & Ratti, 2018). This metric was calculated to measure the range of daily lives of the users, using the following equation:

$$R_g = \sqrt{\frac{\sum_{i=1}^{3}(r_i - r_c)^2}{3}}$$

where r_i is the coordinate of the user's location i, and r_c represents the geometric center of mass coordinates of all the locations for the user. R_g denotes the user's living radius. A larger R_g indicates a larger living range of the user.

4.3. Definition of home-workplace-activity space (H–W-A) spatial separation

Existing studies on jobs-housing relationships and living circles indicated that the proportion of the population within a commuting distance of 5 km can be regarded as an indicator of the jobs-housing balance and effective commuting resources in the region (China Academy of Urban Planning & Design, 2020). With reference to this indicator, we defined the proportion of the population with HWD and HAD and R_g greater than 5 km as the HWS, HAS, and HWAS of a region, respectively, using the following equations:

$$HWS_i = \frac{W_i}{H_i}; HAS_i = \frac{A_i}{H_i}; HWAS_i = \frac{R_i}{H_i}$$

where HWS_i denotes the home-working separation in region i, HAS_i represents the home-activity separation in region i, and $HWAS_i$ represents the home-working-activity separation in region i. W_i, A_i, and R_i denote the number of people with HWD, HAD, and R_g greater than 5 km in region i, respectively; H_i is the total (residential) population in region i.

4.4. Geodetector

The spatial organization of the home, workplace, and activity locations is an important component of urban spatial structure, and the spatial configuration relationship of these locations has an important impact on the development of cities and the lifestyles of the residents. Existing studies have shown that the built environment and socioeconomic attributes are closely related to human activity patterns (Ewing & Cervero, 2010; Maat et al., 2005; Xu et al., 2016). Analyzing the organization of the living space of residents in the context of both, the built environment and socioeconomic parameters, can help us understand the formation mechanism of their daily life structure more comprehensively. Considering the "5D" characteristics of built environment (density, diversity, design, distance to transit, and destination accessibility), while combining the socioeconomic attributes and built environment information, we selected seven categories and 16 sub-categories of variables to construct the influencing factor index system, as shown in Table 2.

Furthermore, the geodetector was applied to analyze the factors

Table 2
Explanations of built environment and socioeconomic variables.

Factors	Variables	Sub-variables	Abbreviations
Built environment	Public service	Density of POIs	X1
		Diversity of POIs	X2
	Accessibility	Road network density	X3
		Bus stop density	X4
		Metro station density	X5
	Location	Distance to the city center	X6
		Distance to the CBD	X7
		Loop location	X8
	Land use	Land use mix	X9
Socioeconomic	Population density	Residential density	X10
		Employment density	X11
	Economic level	House price	X12
		Annual income per employed person	X13
	Population structure	Sex ratio	X14
		Percentage of the workforce	X15
		Percentage of elderly population	X16

Table 1
Sample of experimental data.

ID	Gender	Age	H_lon	H_lat	W_lon	W_lat	A_lon	A_lat
U1	Male	28	40.12xx	116.67xx	39.87xx	116.34xx	40.17xx	116.55xx
U2	Female	37	39.69xx	116.32xx	40.05xx	116.50xx	39.83xx	116.63xx
U3	Male	51	39.97xx	116.09xx	40.12xx	116.23xx	39.99xx	116.46xx

*Note: home (H), workplace (W), major activity places (A), latitude (lat), longitude (lon).

influencing the spatial separation of homes, workplaces, and activity spaces in Beijing. Geodetector is a kind of spatial statistical model used to quantify the influencing effects of potential driving factors on geographical phenomena based on spatial variance analysis (Wang et al., 2010). Generally, they consist of four components: risk detection, factor detection, ecological detection, and interaction detection, and have been widely applied in the physical, ecological, social, economic, and geographical fields (Gao et al., 2021; Wang, Zhang, & Fu, 2016). The main purpose of this study is to understand the determinants of the spatial separation of the homes, workplaces, and activity spaces of the residents and the interactive effects in it; therefore, we employed a factor and interactive detector to examine which factor had a more important impact on the H–W-A separation and how differently the pairs of factors interacted with each other.

5. Results

5.1. Travel characteristics and home-workplace-activity space separations (H–W-A-S) at the subdistrict scale

5.1.1. Spatial distribution of residential, employment, and activity densities

The number of homes, workplaces, and activity spaces of the users identified by the mobile phone data were aggregated into the subdistricts. These three densities were calculated for each subdistrict and divided into five classes based on natural breaks. Fig. 4(a–c) portrays the spatial distribution of the three densities. It was obvious that there were significant spatial clustering characteristics in the high-value areas of all the three types of densities. However, the population density levels portrayed a decreasing trend from the center of the city to the periphery. Specifically, the overall level of residential density was the lowest, and the high-density areas were mainly located between the 2nd and 5th ring roads, which were adjacent to the major employment centers, with a spatially symmetrical pattern (Fig. 4a). In contrast, the overall level of employment density was the highest, and the clustering degree was the most pronounced at the center (Fig. 4b). The high-density areas were mainly clustered in several typical employment centers, such as the central business district (CBD), Beijing Financial Street, and Zhongguancun areas. In addition, the activity density level was relatively high, and urban areas having abundant activity facilities, such as major shopping districts and scenic spots, such as the Beijing workers stadium, Sanlitun, Wukesong, and Olympic Park, tended to have high activity density areas (Fig. 4c). Overall, the north-south distribution of residential density was relatively balanced throughout the study area, but the employment and activity densities were significantly higher in the

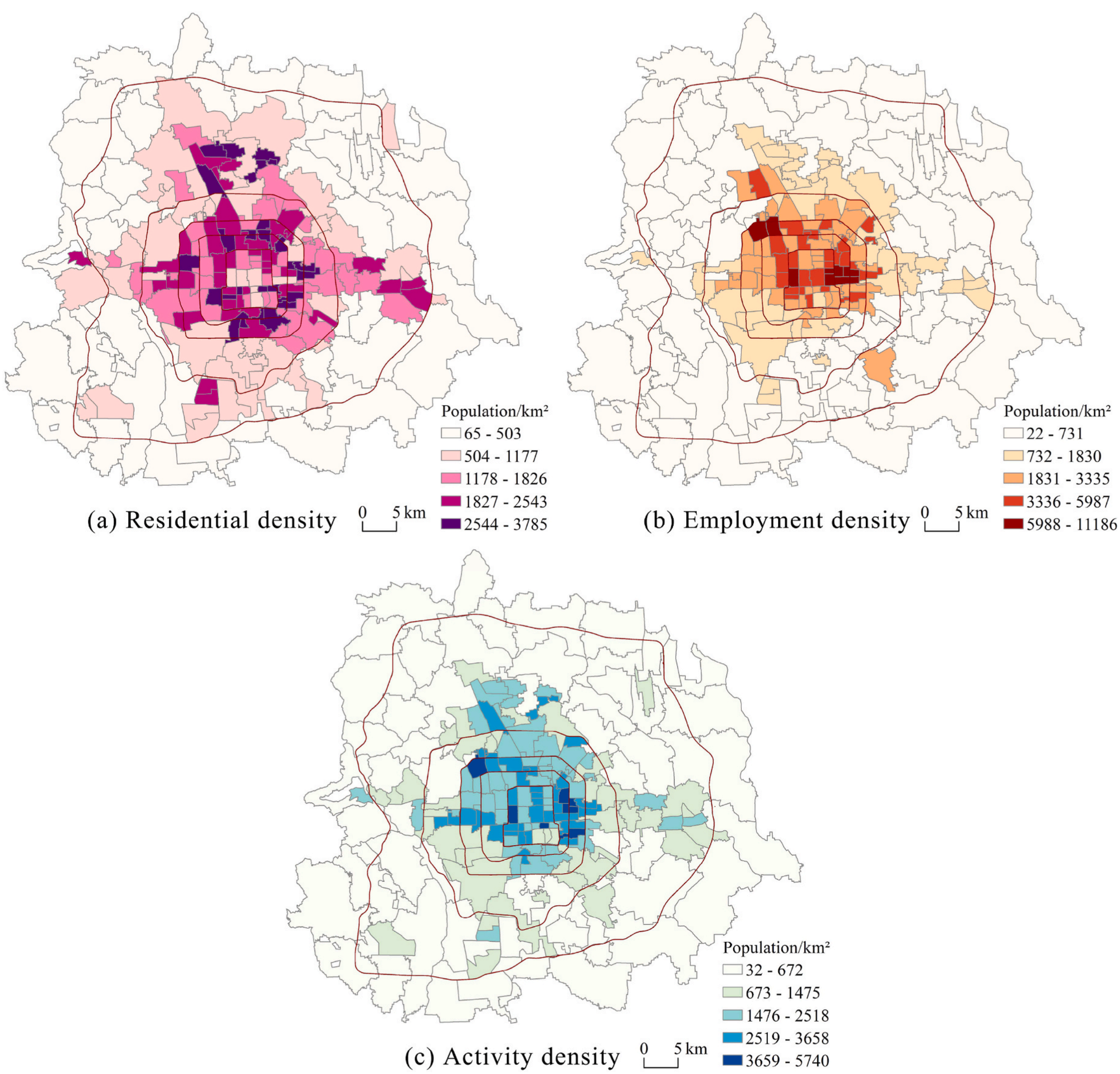

Fig. 4. Spatial distribution of residential, employment, and activity densities.

northern region than the southern area.

5.1.2. Spatial disparities of movement distance and living radius

Fig. 5(a–c) portrays the spatial distributions of HWD, HAD, and R_g, respectively. First, there was an apparent concentric circle structure in the spatial distribution of HWD (Fig. 5a). The closer the subdistrict to the city center, the shorter its HWD, and vice versa. The shortest HWD was for the Qinghuayuan street (7.49 km) and the longest was for the Tiangongyuan street (17.36 km), with an average HWD of 10.92 km. Second, the average HAD was 10.04 km, Tsinghuayuan street had the shortest HAD (7.26 km), and Qinglonghu had the longest HAD (14.35 km). Meanwhile, the HADs of the subdistricts between the 3rd and 5th ring roads and along the 5th ring road were shorter, while the HADs of the subdistricts within the 3rd ring and outside the 5th ring were relatively longer. The overall spatial distribution of the HADs portrayed a sandwich-like structure (Fig. 5b). Furthermore, in terms of the daily living range, the smallest R_g was observed for the Tsinghuayuan street (5.23 km) and the largest was observed for the Tiangongyuan street (9.9 km), with an average R_g of 7.12 km. The spatial distribution of R_g was similar to that of HWD, portraying a significant concentric circle structure (Fig. 5c). Overall, the R_g distribution of the subdistricts was more balanced and relatively concentrated, while the HWD distribution was more varied.

5.1.3. Spatial pattern and hotspot distribution of H–W-A-S

To better capture the spatial differentiation of the H–W-A separation, we adopted the Getis-Ord Gi* index (Getis & Ord, 1992) to measure the statistically significant spatial distribution of the hot and cold spots, based on the calculation of the three types of separation in each subdistrict. First, the average HWS was calculated (0.67), the lowest being 0.46 (Boxing street) and the highest being 0.92 (Junzhuang). This indicated that there was a serious home-working separation in Beijing, with polarization characteristics. According to the cold and hot spot detection results, the hot spot areas of the HWS were mainly distributed in the northwest, east, and a few areas in the south within the 6th Ring Road, while the interior of the 4th Ring Road mainly consisted of cold spot areas (Fig. 6a). This reflected that the HWS in the suburbs was obviously more serious than that in the central city. Second, compared with the HWS, the HAS within each subdistrict was relatively low (the average HAS was 0.49). The HAS was lowest in the Tsinghuayuan street (0.35) and highest in the Junzhuang town (0.78), and the disparities between the subdistricts were relatively small. The spatial distribution of the HAS portrayed that the HAS was relatively high in the 4th Ring Road, relatively low in the subdistricts outside the 4th Ring Road and near the 5th Ring Road, and highest in the subdistricts along the 6th Ring Road (Fig. 6b). Moreover, the number of hot spots of the HAS was relatively small, mainly distributed in the area along the 6th Ring Road,

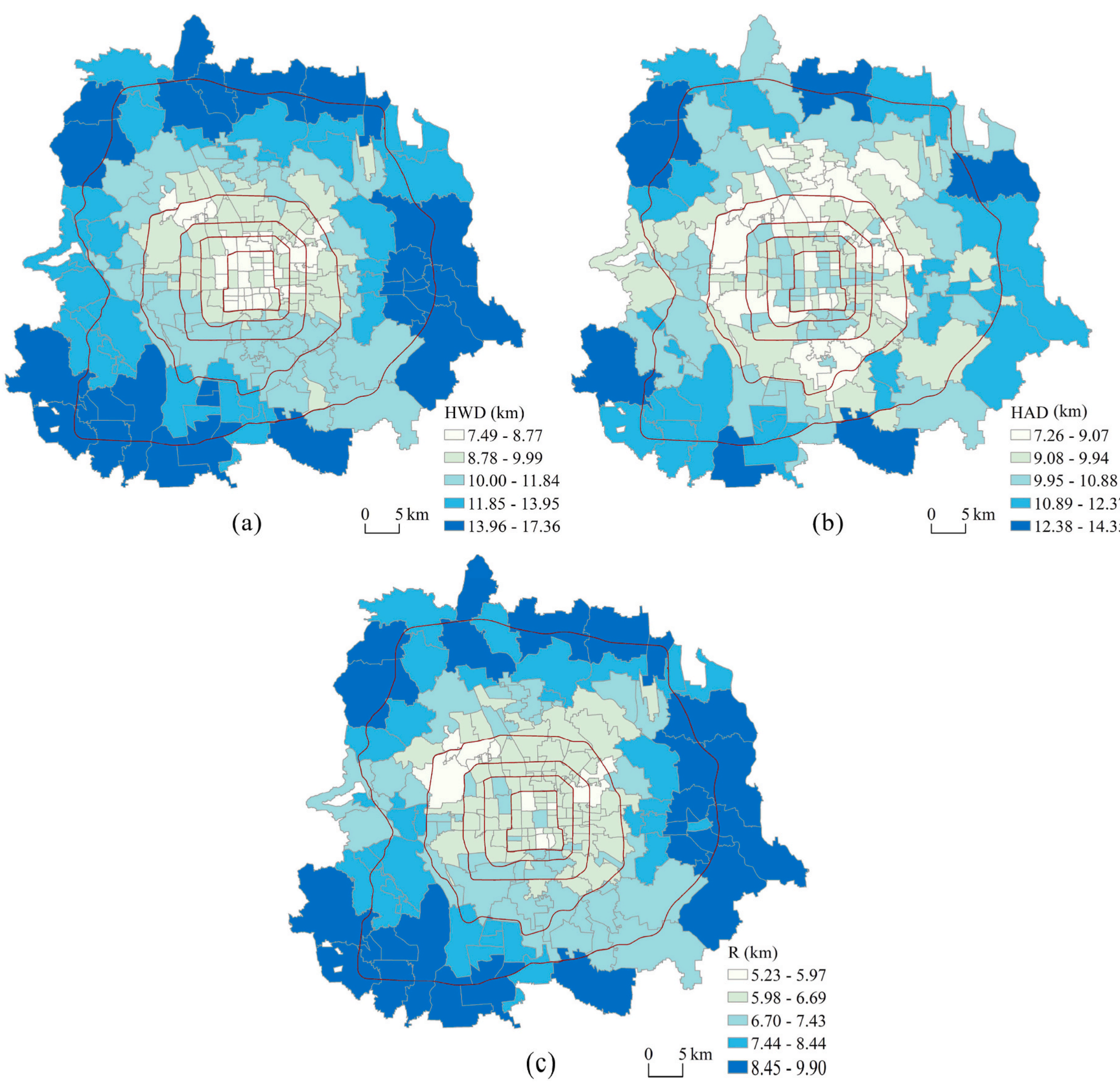

Fig. 5. Spatial distribution of travel distance and living radius of the users with respect to (a) HWD, (b) HAD, and (c) R_g.

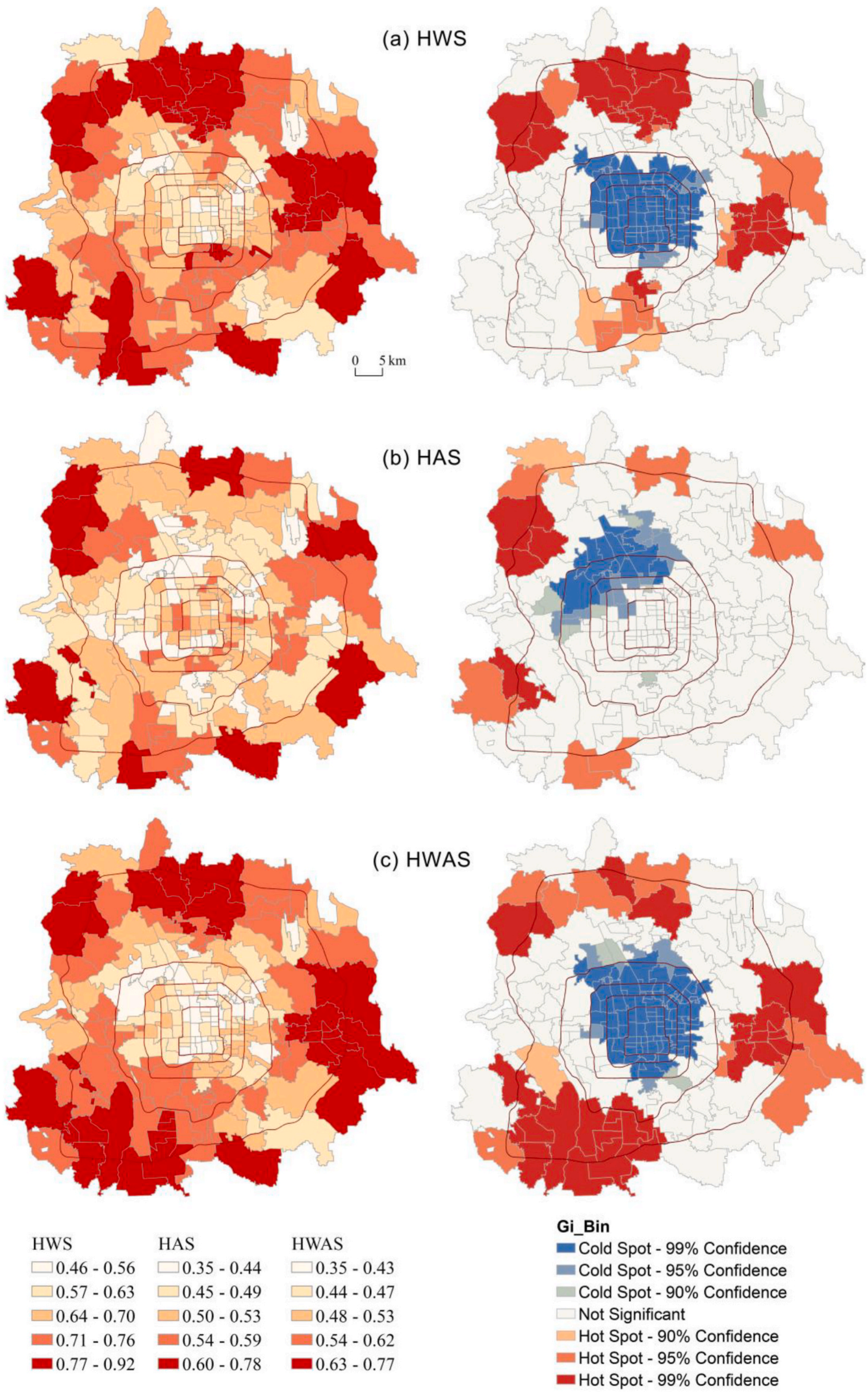

Fig. 6. Spatial patterns of three separation degrees and their hot and cold spot distributions: (a) (HWS, (b) HAS, and (c) HWAS.

while the cold spots were concentrated in the northwestern area from the 3rd Ring Road to the 5th Ring Road. In terms of the HWAS, the distribution range was 0.35–0.77, with an average HWAS of 0.51. The spatial distribution of the HWAS was characterized by a significant concentric-circle structure and portrayed an increasing trend from the center to the periphery (Fig. 6c). Notably, the HWAS hot spots formed three major groups, distributed in the northwestern, southwestern, and eastern areas. The cold spots were located within the 4th Ring Road and north of the 5th Ring Road. In short, the degree of HAS was relatively low, followed by HWAS, the HWS was the highest.

5.2. Travel characteristics and H–W-A-S of different groups

5.2.1. Travel characteristics of different groups

Table 3 shows and compares the travel indicators of different populations. Overall, the average HWD, HAD, and R_g of users are 11.75 km, 10.11 km, and 7.37 km, respectively, and the average monthly work frequency (MWF) and monthly activity frequency (MAF) are 23 and 11, respectively. In terms of gender attributes, the travel distances and visit frequencies of men were greater than women, with HWD, HAD, and R_g being 0.89 km, 0.51 km, and 0.39 km longer for males than females,

Table 3
The travel indicators of different groups.

		HWD (km)	MWF	HAD (km)	MAF	R_g (km)
Total		11.75	23.05	10.11	11.3	7.37
Gender	Male	12.09	23.8	10.34	11.57	7.54
	Female	11.2	21.68	9.83	10.72	7.15
Age	≤18	10.59	23.11	9.6	11.29	6.79
	19–34	11.87	23.4	10.22	11.19	7.45
	35–59	11.78	22.75	10.13	11.37	7.4
	≥60	11.09	21.44	9.99	11.05	7.14

respectively, while HWF and HAF were 2 and 1 times higher for males than the females, respectively. It shows that the travel differences between male and female groups were not significant. Moreover, all users were divided into four groups by age stage: teenagers (≤18 years old), young people (19–34 years old), middle-aged people (35–59 years old), and elderly people (≥60 years old), and then the travel characteristics of the four groups were counted. Table 3 shows that the three types of distances for young people are the longest among all four groups, followed by middle-aged people and elderly people, while the three types of distances for teenagers are the shortest among all four groups. Meanwhile, there were some age differences in MWF of users, but no significant differences in MAF.

5.2.2. H–W-A-S of different groups

The three separation degrees of different groups are shown in Table 4. On the whole, the jobs-housing misbalance is the most serious, the average HWS is 0.72, significantly higher than HAS (0.52) and HWAS (0.56). Specifically, there is a very small difference between the three separations for men and women, and the separation for men is only 1%–2% higher than the separation for women. In addition, the highest HWS and HWAS were found in young adults with 0.73 and 0.57, respectively, and the largest HAS was in middle-aged people (0.53). Overall, there was little difference in spatial separations among the various groups.

5.3. Influencing factors of home-workplace-activity space (H–W-A) separation

Since the separations between various groups are small but significant at the subdistrict scale, the three separations of each subdistrict unit were selected as dependent variables. Then, we carried out an attribution analysis by considering the distribution of population structure, neighborhood built environment, and other socio-economic attributes, and comprehensively analyzed the key factors and effects of H–W-A-S. The factor detector and interactive detector were applied to reveal which factor had a more important impact on the H–W-A separation and how differently the pairs of factors interacted with each other. Three attribution analyses were conducted using HWS, HAS, and HWAS as dependent variables, along with the 16 sub-variables presented in Table 2 as the independent variables. The results are presented as follows.

Table 4
Three separation degrees of different groups.

		HWS	HAS	HWAS
Total		0.72	0.52	0.56
Gender	male	0.72	0.53	0.57
	female	0.71	0.51	0.55
Age	≤18	0.64	0.50	0.49
	19–34	0.73	0.52	0.57
	35–59	0.71	0.53	0.55
	≥60	0.67	0.52	0.52

5.3.1. Factor detection analysis

As shown in Fig. 7, the results of factor detection for HWS, HAS, and HWAS, and 11, 5, and 14 of the corresponding 16 variables passed the significance test, respectively, and there were significant differences between the explanatory power of different variables. Specifically, for HWS, house price (X12) was the primary factor that affected the HWS, its explanatory power was 0.45. Accessibility was the secondary factor, with road network density (X3) and bus stop density (X4) having explanatory powers of 0.38 and 0.22, respectively. In addition, employment density was also an important influencing factor for HWS, with a factor explanatory power of 0.32.

For HWAS, house price (X12), distance to the city center (X6), and road network density (X3) were the three main factors, with the factor explanatory powers of 0.58, 0.53, and 0.39, respectively. This indicated that the economic status, accessibility, and location conditions of the subdistricts significantly influenced the HWAS. However, in terms of HAS, only five variables passed the significance test, namely, residential density (X10), road network density (X3), gender ratio (X14), house price (X12), and distance to the city center (X8). This demonstrated that the degree of separation between the homes and activities of residents was strongly influenced by factors, such as house price, demographic structure, accessibility, and location conditions, whereas there was no direct correlation with the other factors mentioned in Table 2.

5.3.2. Interaction detection analysis

Fig. 8(a–c) portray the interaction detection results between the factors of HWS, HAS, and HWAS, respectively (the variables that did not pass the significance test were excluded). The results indicated that the explanatory power of any two factors of HWAS, HWS, and HAS after interactions as greater than the explanatory power of single factors, indicating that the separation degree was jointly governed by various factors of the built environment and socioeconomic attributes. Specifically, the interaction types of HWS included bi-factor enhancement (wherein the explanatory power of interactions was stronger than the explanatory power of the single factor but not higher than the sum of the two factors) and nonlinear enhancement (wherein the explanatory power of the interactions was higher than the sum of the explanatory power of the two factors). The top three factors interactions were for that of house price (X12) ∩ percentage of the workforce (X15), house price (X12) ∩ percentage of elderly population (X16), and house price (X12) ∩ residential density (X10). For HAS, the factor interactions were all bi-factor enhancements, and the strongest interaction was house price (X12) ∩ sex ratio (X14). In addition, with respect to the HWAS, the top four explanatory power of the interaction factors were: house price (X12) ∩ X6 (distance to the city center), house price (X12) ∩ loop location (X8), house price (X12) ∩ percentage of the workforce (X15), and house price (X12) ∩ percentage of elderly population (X16). The above results demonstrated that house prices had a dominant impact on the spatial organization of the daily lives of residents. The impact of demographic structure was relatively weak on the separation degree when it acted independently, while its explanatory power increased nonlinearly when it acted together with other factors, especially house price and location factors.

6. Discussion and conclusions

Owing to rapid informatization and the increasing urban sprawl, metropolitan residents are facing challenges of spatial imbalance between their home, workplace, and activity space locations. Particularly, the increased commuting distances and the resulting longer daily commuting times not only cause severe traffic congestion in cities, but also affect the quality of life and subjective well-being of urban residents. In this context, existing studies have conducted extensive explorations of daily activity spaces of residents and their spatial separation (Shen et al., 2021). However, existing studies do not consider the relationship between the home, workplace, and activity space and the

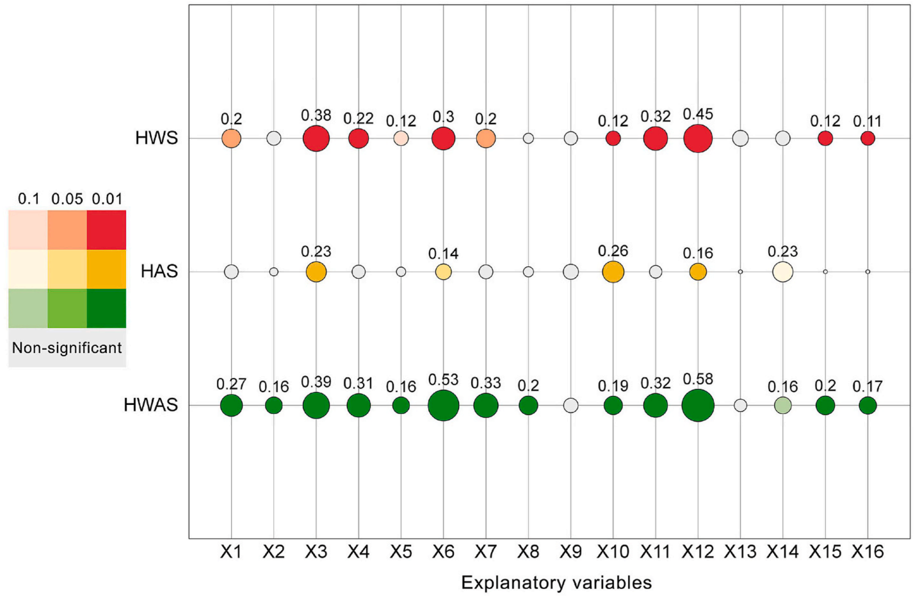

Fig. 7. Factor power (q) values of explanatory variables with respect to HWS, HAS, and HWAS.*Note: 0.1: Significant at the 10% level; 0.05: Significant at the 5% level; 0.01: Significant at the 1% level.

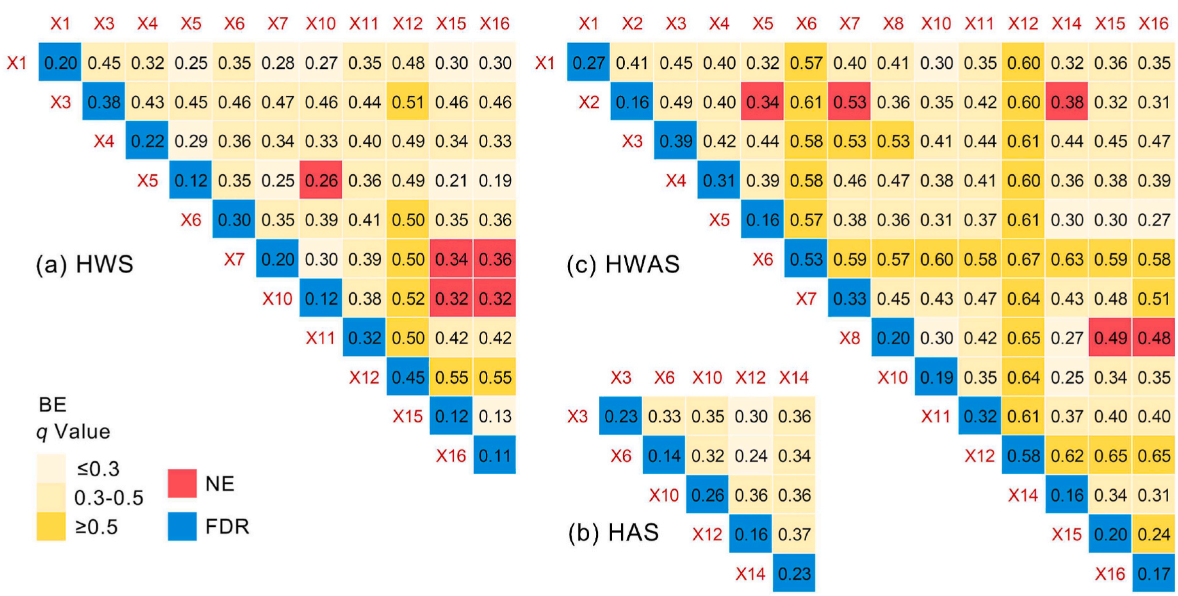

Fig. 8. Interaction detector results of different factors for (a) HWS, (b) HAS, and (c) HWAS *Note: BE (Bi-factor enhancement) $q\ (X1 \cap X2) > \text{Max}\ (q(X1), q(X2))$; NE (nonlinear enhancement): $q\ (X1 \cap X2) > q(X1) + q(X2)$; FDR: Factor detector results.

mechanisms influencing their spatial separation degree. Therefore, in this study, we provided empirical evidence of the relationships between the H, W, and A spaces, while considering Beijing, China, as our study area. Using the mobile phone signaling data of the residents of Beijing for May 2019, we identified the home, workplace, and major activity spaces of more than 2.3 million Beijing residents, and conducted a detailed measurement and spatial analysis of the separation degree with respect to these three spaces. We also explored the influencing mechanisms of geographical context (including built environment and socio-economic factors) on the spatial separation of the daily living spaces of residents. Our findings are as follows:

First, the spatial distribution of the residential, employment, and activity densities had significant spatial clustering characteristics and presented a more obvious socio-spatial differentiation. Specifically, high-density employment and activity areas were mainly located in the northern part of the central city. This feature may be closely related to the imbalance of socio-economic development between the north and the south regions of the city (major employment centers and commercial centers were mostly distributed in the city center and the north).

Second, the range and spatial separation of the daily living space of the residents was relatively large, among which HWS was the highest, followed by HWAS (second) and HAS (lowest), all three types of separation had significant spatial differentiation characteristics. Specifically, the average HWD in Beijing in 2019 was 10.92 km, and the HWS was 0.67, indicating a severe job-housing imbalance in Beijing. Notably, both the indicators of the home-working space are very close to the relevant indicators in the *2020 National Commuting Monitoring Report for Major Cities* published by the China Academy of Urban Planning & Design (2020) (the average commuting distance in Beijing in 2019 was 11.1 km, and the proportion of 5-km commuting was 38%). This also indicated that our findings were reasonable. In terms of the daily living space of residents, the average living radius was 7.12 km, and the range of HWAS was 0.35–0.77, which was more concentrated and balanced compared with HWS and HAS. In general, there was similarity in the spatial distribution of the three types of separation (i.e., low separation in urban centers and high separation in suburban areas), reflecting the close relationship between the daily living spaces of residents and the regional economic level.

Third, although men exhibited higher travel indicators (distance, frequency, and spacing) than women, the difference between gender and age between various groups was relatively small. Yet, this finding does not quite line up with previous relevant studies, especially in Western cities. According to previous studies of Western cities, the commuting distance and time of employed women are lower than men because women have more domestic responsibilities in the household, especially child care (McQuaid & Chen, 2012; Roberts, Hodgson, & Dolan, 2011). Moreover, there are significant differences in commuting behavior and activity patterns between men and women in Western cities (Kwan, 1999a; 1999b; 2000). Conversely, there is no significant gender difference in travel characteristics and spatial separations among urban residents in Beijing. By comparing with previous related studies, we found similar findings in Chinese megacities including Beijing, Guangzhou, and Shanghai (He, Zhou, & Xie, 2017; Liu, Yan, Fang, & Cao, 2008; Meng, Zheng, & Yu, 2011). It might be linked to social inclusiveness and high life stress levels in Chinese megacities. Nowadays, the cost of living and employment pressure is high in Chinese megacities, where most women work full-time like men, and families are dominated by dual-earners. Meanwhile, along with the increasing social diversity and tolerance, more men are involved in the division of household tasks, and the spatiotemporal constraints of female workers' household roles on their daily travels are gradually decreasing (Chen, Zhou, Li, & Zhan, 2021). Furthermore, Beijing is a megacity with a high concentration of residential, employment, and activity populations, especially since most jobs are concentrated in some specialized science-technology parks and economic development zones. The spatial clustering of employment opportunities and major activity facilities reduces the disparity in access to employment and activities between male and female employees, further lowering the travel distance and spatial separations between male and female workers. In addition, the rapid development of mobile technologies (e.g., mobile maps) and the continuous improvement of public transportation systems have narrowed gender gaps in sense of direction and space, increasing women's travel capacity and frequency. It compensated for gender-based disparities in trip characteristics, resulting in a progressive equalization of travel characteristics between men and women (Zhang & Feng, 2021).

Finally, the attribution analysis indicated that housing price was the dominant factor affecting the separation degree of the daily living spaces of residents, while accessibility and location also had important effects on the separation degree. Meanwhile, the factor interaction results revealed that the degree of separation of the daily living spaces of residents was governed by a combination of built environment and socioeconomic factors. These findings were consistent with those of some previous studies (Huang & Wong, 2016; Wang, Li, & Chai, 2012; Zhao, 2013). However, unlike some previous studies (Maoh & Tang, 2012; Dang, Dong, Yu, Zhang, & Chen, 2015), we found that there was no direct causality between the land use mix near the dwelling areas and the income level of residents and their separation degree with respect to the daily living space of residents (land use mix (X9); the annual income per employed person (X13) did not pass the significance test). Interestingly, this finding was similar to the findings of Xu et al. (2018) with respect to Singapore and Boston. They found that the economic level was not a limiting factor for travel and activities. We argue that in highly developed megacities having efficient public transportation systems, such as Beijing, Singapore, and Boston, the travel and activities of residents are so convenient and flexible that the impact of individual income levels on the separation degree of daily living space of residents can be limited. However, for cities that are less developed or have less developed public transportation, it is possible that the interrelationship between individual socioeconomic attributes and living space of residents is more complex.

The major contributions of this study are twofold. Firstly, this study is the first to estimate the degree of spatial separation between the H, W, and A locations and analyze their correlation with geographic context. In contrast, previous studies have mainly explored the dual-space from the perspective of the jobs-housing relationship, such as jobs-housing balance and segregation (Long & Thill, 2015; Zhao, Lü, & De Roo, 2011). Scholars have recently begun to focus on the out-of-home non-employment activity space, and have conducted multi-agent, multi-scale, and multi-contextual studies on the spatial differentiation of residents' living spaces and urban structure, thanks to the rapid development of new technologies and the emergence of various big data (Park & Kwan, 2018; Shen, 2019; Ta, Kwan, Lin, & Zhu, 2021; Zheng et al., 2021). Then, a new perspective and approach to detecting and designing urban living structure was proposed (Jiang & Huang, 2021). Nevertheless, most existing studies still focus on analyzing the spatial distribution and pattern of residents' daily activities from the scale or density perspective, lacking a common focus on residential, employment, and other activity spaces. This study explored the interrelationships among the three types of spaces, as well as the influencing factors of their relationships, which breaks the fundamental dualism of the jobs-housing relationship. It can be useful to improve the theoretical interpretation and scientific understanding of the spatial interrelationship of the homes, workplaces, and other activity spaces in the context of rapid urbanization, which has achieved a simultaneous innovation in terms of research perspective and content in the urban space research field.

In addition, the findings of this study can support the urban planning and development of Beijing in four dimensions. First, this study identified the homes and workplaces of Beijing residents more than 2.3 million based on mobile phone signaling data, the sample size of which exceeds 10% of the city's entire population. Previous censuses and surveys were unable to achieve the same level of scale and accuracy. Therefore, this study could provide a more comprehensive picture of the current jobs-housing pattern in Beijing, which is a crucial basis for various urban planning. Furthermore, by calculating the mutual spatial distance between homes, workplaces, and activity spaces of Beijing residents and evaluating the corresponding spatial separation degree at the subdistrict level, this study was able to optimize the original dualistic understanding of the jobs-housing relationship from a cognitive standpoint. It also contributes to improving the scientific understanding of the spatial relationship between residential, employment, and activity spaces in the development and planning of urban space in Beijing. Moreover, this study highlighted three critical factors that have a significant impact on the spatial separation of residents in Beijing: housing price, accessibility, and location. By precisely measuring the independent and interactive effects of each influencing factor, this study can provide feasible planning strategies for a more precise and effective resolution of the geographical separation of residents. Additionally, this study revealed the spatial separation of home-working-activity at the subdistrict scale, which can provide important guidance and reference for effective policy formulation and implementation in the construction of a livable city, community living circle planning, and spatial structure optimization in Beijing. Especially for areas having high degrees of separation, targeted policy measures can be taken to improve them according to the differences in their influencing factors (e.g., improving the accessibility of public transportation and the configuration of public service facilities).

This study has several limitations. 1) Due to the complexity and diversity of the types of activity spaces themselves, we considered the places not related to work or home, where residents stay most frequently in a month, as their main activity places, and explored the spatial relationships of the three most important locations in a typical resident's daily living spaces. However, some residents may have multiple places of residence and work, our findings do not cover such users. In a subsequent study, further integration of multiple source data for validation is needed to improve the scientific and generalizability of the results. 2) Most of the variables of HAS failed to pass the significance test, which indicated that the influence mechanism of HAS was more complex than that of HWS and HWAS. It was relatively insufficient to explain HAS only from the built environment and socioeconomic factors at the subdistrict level. Future studies need to consider the diversity and complexity of residents of different social classes and their activity spaces more comprehensively, while selecting more detailed information indicators of individual attributes for in-depth exploration. 3) In this study, we only used distance as an assessment criterion to measure the degree of spatial separation, which is limited to a certain extent. In future studies, travel and activity time should be included in the assessment system to enhance the comprehensiveness and scientific validity of our study findings.

Declaration of competing interest

None.

Author statement

Jian Liu: Conceptualization, Investigation, Methodology, Data curation, Formal analysis, Writing - original draft, Visualization, Writing - Review & Editing, Bin Meng: Conceptualization, Methodology, Resources, Writing - original draft, Supervision, Writing-reviewing and editing, Funding acquisition. Ming Yang: Investigation, Data curation, Writing-reviewing and editing, Funding acquisition, Project administration. Xia Peng: Methodology, Resources, Validation, Visualization. Dongsheng Zhan: Methodology, Roles/Writing - original draft. Guoqing Zhi: Software, Visualization.

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